

Statistical report

This document sets out our statistical model’s assumptions, explains its implementation and presents the results.

Model assumptions

The aim of this analysis is to describe timecourse data about the density of CHO cell cultures that were given treatments that induce cell death. Some cultures were given genetic interventions that aim to make them apoptosis-resistant, either by reducing the rate at which they die or by extending the period before they start to die. We would like to know which interventions have the most effect, and in what way.

Assumptions about the target system

We assume that in this scenario the cells exist in four states:

- R replicative, growing at a rate of $\mu R(t)$, where t is the current time and $R(t)$ is the current density of replicative cells
- Q_a growth arrest, transferring from normal at a rate of $k_q R(t)$
- Q_c death committed, transferring from growth arrest at a rate of $k_q R(t-\tau)$, where $\tau > 0$ represents the delay between growth arrest and death commitment.
- dead, transferring from death committed at a rate of $k_d Q_c(t)$, where $Q_c(t)$ is the density of death-committed cells at time t .

These assumptions define a system of ordinary differential equations (specifically “delay differential equations”) that can be solved analytically, so that the density at a given time can be found as a function of the parameters μ , τ , k_q , k_d and the initial density of replicative cells R_0 .

We have measurements of the total cell volume, i.e. $R(t) + Q_a(t) + Q_c(t)$ at several time points, for cell cultures with the following structure:

- 9 genetic designs, comprising 7 genetic interventions and two control designs.
- Between 1 and 4 clones implementing each design
- Two technical replicates for each clone.

Replicates of the same clone are biologically identical, though we expect some variation in measurements due to the experimental conditions. Clones with the same design are expected to be similar, with some degree of clonal variation that may differ depending on the design. There is no prior information distinguishing the designs from each other, or distinguishing clones with the same design.

Given these assumptions a multi-level Bayesian statistical model is appropriate.

Multilevel model structure

We used the following measurement model:

$$y \sim \text{lognormal}(\log(\hat{y}(t, R0, \mu, \tau_r, k_{qr}, k_{dr})), \sigma)$$

where

- $R0$, τ_r , k_{qr} and k_{dr} are vectors of replicate-level parameters
- μ is an unknown number representing the pre-treatment growth rate, which we assume is the same for all replicates.
- σ is an unknown log-scale error standard deviation
- t is a vector of known measurement times (one per measurement)
- \hat{y} is a function mapping parameter configurations to densities, under the delay differential equation assumptions laid out above

The parameters τ_r , k_{qr} and k_{dr} vectors are treated as compounds of a global mean and design and clone level residuals, i.e.

$$\begin{aligned}\tau_r &= \alpha_\tau + \beta_\tau + \gamma_\tau \\ k_{qr} &= \alpha_q + \beta_q + \gamma_q \\ k_{dr} &= \alpha_d + \beta_d + \gamma_d\end{aligned}$$

where the α parameters are global means, the β s are design-level residuals and the γ s are clone-level residuals.

In order to accommodate uncertainty as to the level of clonal variation, we use hierarchical prior distributions for the clone level parameters, e.g.

$$\gamma_\tau \sim \text{normal}(0, sd_\tau)$$

Other unknowns have informative prior distributions based on scientific knowledge.

Results

Observed vs modelled timecourses

Figure 1. shows observed timecourses for each design under the 15ug/mL puromycin treatment, alongside a sample of model-realised timecourses. The modelled and observed timecourses appear qualitatively similar, suggesting that the model is not dramatically mis-specified.

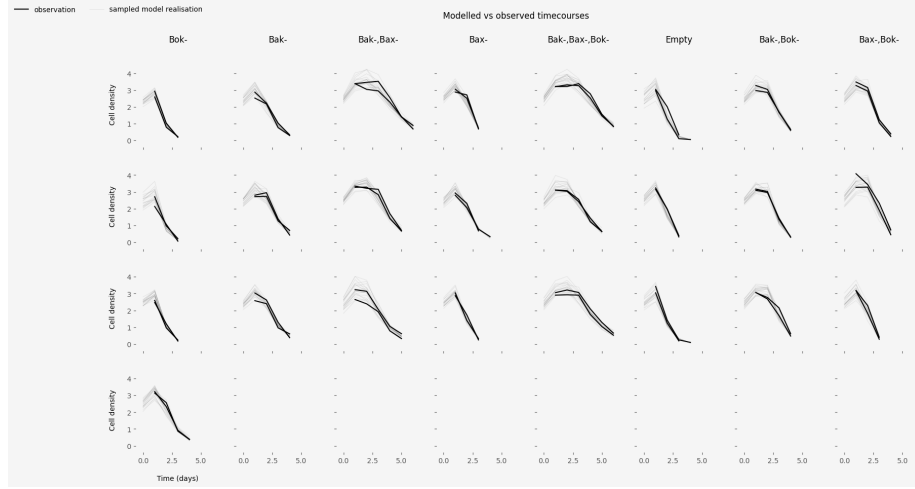


Figure 1: Simulated timecourses for the 15ug/mL Puromycin treatment

Posterior distributions of design parameters

Figure 2. plots the 2.5% to 97.5% marginal posterior intervals for the design-level parameters, relative to the control experiment. According to our model, some designs are probably different from the control with respect to the τ and k_d parameters. On the other hand, all of the posterior intervals for design-specific effects on the parameter k_q include zero, showing that the designs cannot conclusively be distinguished using the data provided.

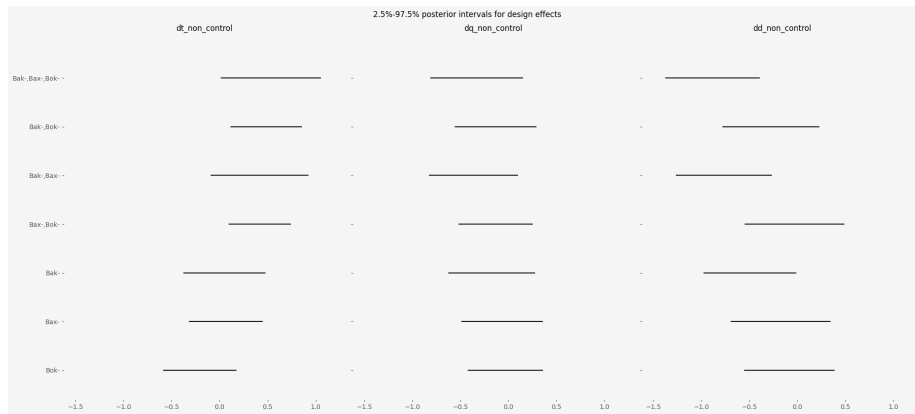


Figure 2: Posterior intervals for design level parameter